

**Workshop on Consumer and Investor Decision-Making and the Use of Expectations
TRANSPORTATION DEMAND SECTOR**

David L. Greene
Paul N. Leiby

December 27, 2007

“However, the essence of models is deliberate simplification. Reality thus is more complex than the model.” Gordon, p. 679

I. Introduction

This paper examines how consumers and firms make decisions that have important implications about transportation energy use in the face of uncertainty, and how they form expectations that influence those decisions. These issues are considered with reference to how such behavior is represented in the Transportation Sector Module of the National Energy Modeling System (NEMS). Consumers and firms make decisions about the types of vehicles they will purchase, how fuel efficient the vehicles should be, what type of fuel will be used to power them and how much they will be used. Manufacturers decide what kinds of vehicles to offer for sale, how fuel efficient they should be, and what fuels should power them. These decisions involve monetary costs and benefits, as well as trade-offs among non-monetary attributes. All of these decisions are made in the context of uncertainty about the future in which the vehicles will be purchased and used.

Human beings form expectations as a means of coping with uncertainty about the future. If there were no uncertainty, expectations would always correspond to reality, which is to say humans would possess perfect foresight. Perfect knowledge of the future constitutes one extreme of expectations. Another extreme, perfect myopia, assumes that no information is available to improve on the prediction that the future will be like the present. In between lie an infinity of possible ways of formulating expectations about the future. In the realm of economics both consumers and producers form expectations about the future to guide their decision making in the present. Individuals may form a single expectation about the future or may hold several different expectations simultaneously (leading to hedging behavior). How a formal model such as NEMS ought to represent the expectations of consumers and firms is a complex question that depends partly on what is known about how economic agents form expectations, partly on the importance of expectations in energy markets, and partly on the purposes for which the model was built. These are extremely complex issues to which the authors are not able to provide definitive answers. We hope that we provide useful insights that will help advance the state of discourse.

NEMS is a computer-based energy-economic modeling system of U.S. energy markets through 2030 (EIA, 2007a). It represents engineering and economic relationships via mathematical equations and algorithms in order to project the production, import, conversion, consumption and prices of energy in U.S. markets. Exogenous to the models

computations are key assumptions about the macroeconomy and demographics, world energy markets, technologies and technological change and consumer preferences. The explicit incorporation of engineering relationships and technological change is a key feature of the model. In addition to developing projections of U.S. energy markets for a variety of uses, NEMS is frequently used to evaluate impacts of proposed energy policies, such as carbon or energy taxes, and energy efficiency standards.

The Transportation Sector Module represents energy demand, or end use, by the U.S. transportation sector within NEMS. It is comprised of four modules: Light-Duty Vehicles, Air Travel, Freight Transport, and Miscellaneous Energy Use. Its two main objectives are to provide projections of transportation energy demand by fuel type, by mode of transport and region in a way that is sensitive to technological change (EIA, 2007b, p. 3):

1. Generate projections of transportation energy demand at the national and the census division levels.
2. Endogenously incorporate various technological innovations, macroeconomic feedback, infrastructural constraints, and vehicle choice in making projections.

Key inputs to the NEMS model are, 1) the macroeconomic and demographic factors exogenous to the NEMS model itself, 2) fuel prices not estimated endogenously within NEMS (e.g., the world price of oil) and, 3) technology, consumer preference and policy assumptions developed by the NEMS modelers but exogenous to the Transportation Sector Module (TSM). The TSM supplies estimates of regional fuel consumption by fuel type to NEMS. Prices and quantities are exchanged iteratively between the NEMS model and the TSM until the larger NEMS model reaches a solution.

The model documentation makes it clear that predicting the future, as such, is not the purpose of NEMS. Rather, its intended purpose is to make “projections”, subject to key assumptions about the states of the economy, world energy markets and technological change, and to estimate the impacts of certain actions or decisions, most notably government policies, on these “projections”. We have put the word projections in quotations in the previous sentences because the words forecast, prognosis and prediction are synonyms for it. However, the NEMS modelers are trying to make a distinction that is clearly important to them. They do not intend that NEMS outputs be considered their best assessment of what will happen in the U.S. energy market. Instead, it appears, they intend their projections to be their best assessment of what would happen IF the many assumptions that are inputs to their models were to hold, and if there were no “surprises” that changed the fundamental but often unstated institutional and behavioral premises of their models.

Thus, our first inference about the NEMS Transportation Module and its treatment of uncertainty and expectations is that uncertainty is intended to be reflected by choosing alternative input assumptions. To reflect future uncertainty, NEMS modelers construct scenarios that are structured sets of alternative input assumptions. Scenarios can be and are constructed for special purposes, but are regularly constructed to reflect alternative oil

price and macroeconomic assumptions. Economic agents in NEMS respond differently to the different assumptions, producing alternative projections.

Models are inherently simplifications of reality designed for specific analytical purposes. Therefore, it is meaningless to point out that a model does not perfectly represent the way that real agents form their expectations and make their decisions. The important question is whether such imperfections are important to the purposes of the model and whether it is possible to more accurately represent both the uncertainties and the way economic agents respond to them.

Outline of the paper

The remainder of this report is organized as follows. Section II provides a brief overview of energy use in the transportation sector and the key sources of uncertainty that affect transportation decisions. Section III discusses what is known about how key transportation decisions that affect energy use are made by consumers and firms. Section IV summarizes the history and state of the economic art in modeling expectations. Section V considers how expectations about the future are formed, first looking at empirical, theoretical and experimental evidence for different kinds of expectations, and then looking at how some energy economic models represent expectations. Section VI considers ways that expectations affecting key energy decisions are formed in the NEMS Transportation Sector Module. Finally, Section VII concludes with summary observations on representing transportation investment decisions affecting energy use and the representation of expectations and foresight in those decisions.

II. Energy Use and Uncertainty in the Transport Sector

Given the stated purposes of NEMS, our focus should be on the investment decisions by firms and consumers that are likely to have the greatest impact on the quantity, type and cost of energy use. We now turn to considering the kinds of uncertainty that appear to be most important to transportation energy markets and begin with a brief review of how energy is used in the transportation sector and historical trends in the key variables.

II.1 U.S. Energy use by mode and fuel type

Road transport accounts for most of transport energy use: almost 75% in 2005 (Table 1). Within the highway mode light-duty vehicles (passenger cars and light trucks) predominantly purchased by or for individuals account for the largest share of energy use, 58.4% of total transportation energy. Medium and heavy trucks, purchased primarily by firms, account for nearly half of the rest, 15.5% of total sector energy use. Air transport, dominated by domestic and international air carriers, is a distant second after road transport, accounting for only 8.4% of total transportation energy use. General aviation comprises less than 10% of air transport energy use and only a fraction of that can be attributed to personal aircraft. The third largest component of transport energy use (7.4% of total) is labeled “OFF HIGHWAY” in Table 1, and comprises a mixture of ambiguous

uses (e.g., agricultural, mining and construction equipment, as well as recreational vehicles like snowmobiles) that NEMS represents in several sectors. The remaining energy use is distributed among water 4.6%, pipeline 2.8%, and rail 2.2%.

The gross structure of transportation energy use is appropriately reflected in the structure of the Transport Sector Module, which represents the light-duty vehicle market and decision-making therein in the greatest detail, includes a freight module that pays greatest attention to highway freight, and represents air travel with another module.

Table 1
Domestic Consumption of Transportation Energy by Mode and Fuel Type, 2005^a
(trillion Btu)

	Gasoline	Diesel fuel	Liquified petroleum gas	Jet fuel	Residual fuel oil	Natural gas	Electricity	Total
HIGHWAY	17,280.00	4,683.50	62.9	0	0	15.6	0.7	22,042.7
Light vehicles	16,813.5	414.1	47.5	0	0	0	0	17,275.1
Cars	9,089.0	51.2						9,140.2
Light trucks ^b	7,697.6	362.9	47.5					8,108.0
Motorcycles	26.9							26.9
Buses	6.5	167.7	0.2	0	0	15.6	0.7	190.7
Transit	0.2	76.3	0.2			15.6	0.7	93.1
Intercity		28.3						28.3
School	6.3	63.1						69.4
Medium/heavy trucks	460.0	4,101.7	15.2	0	0	0	0	4,576.9
NONHIGHWAY	244.1	925.6	0	2,437.70	825.8	602.9	316.4	5,352.5
Air	38.9	0.0	0	2,437.70	0	0	0	2,476.6
General aviation	38.9			203.5				242.4
Domestic air carriers				1,861.50				1,861.5
International air carriers ^c				372.7				372.7
Water	205.2	335.1			825.8			1,366.1
Freight		292.7			825.8			1,118.5
Recreational	205.2	42.4						247.6
Pipeline	0.0	0.0	0	0.0	0	602.9	239.5	842.4
Rail	0.0	590.5	0	0.0	0	0	73.1	663.6
Freight (Class I)		571.4						571.4
Passenger		19.1					73.1	92.2
Transit		0.0					44.9	44.9
Commuter		10.6					15.3	26.0
Intercity		9.1					5.5	14.6
HWY & NONHWY TOTAL	17,524.1	5,609.1	62.9	2,437.7	825.8	618.5	317.2	27,384.6
OFF-HIGHWAY	733.8	1,469.6	0	0.0	0	0	0	2,203.4
Agriculture	42.2	464.9						507.1
Industrial & commercial	216.6	248.9						465.5
Construction	34.2	741.6						775.8
Personal & recreational	440.5	5.8						446.3
Other	0.3	8.4						8.7
TOTAL	18,257.9	7,078.7	62.9	2,437.7	825.8	618.5	317.2	29,588.0

Source:

Davis and Diegel, 2007. Transportation Energy Data Book, Ed. 26, Table 2.5

^a Civilian consumption only. Totals may not include all possible uses of fuels for transportation (e.g., snowmobiles).

^b Two-axle, four-tire trucks.

^c 2000 data. 2001 data are not yet available.

^d One half of fuel used by domestic carriers in international operation.

II.2 Key sources of uncertainty

In the authors' opinion, there are four principal sources of uncertainty for decision-making within the TSM that are currently treated as exogenous to the model itself:

1. Energy prices, in particular the world price of petroleum,
2. Technological change both for transportation equipment and fuels,
3. Government policy for transportation and energy and,
4. Consumers' preferences for vehicles and travel.

The price of oil is clearly a major cause of uncertainty for decision-making about transportation investments. Indeed, it does not appear to be possible to predict the price of oil with any useful degree of confidence. As Figure 1 shows, real oil prices fluctuated almost entirely within a range of \$10-\$20 per barrel (2006 \$) until 1974. Since then, the OPEC cartel has had a powerful but virtually unpredictable impact on world oil prices. Figure 1 also shows the three oil price cases considered by the 2007 Annual Energy Outlook (EIA, 2007c). The three cases appear to approximately span the range of historical oil prices since 1974, but do not reflect their volatility in any meaningful sense. This is extremely significant with respect to modeling the formation of expectations by consumers and firms about future oil prices. If oil price paths are not modeled realistically, what will be gained by modeling consumers' and firms' expectations about future petroleum prices?

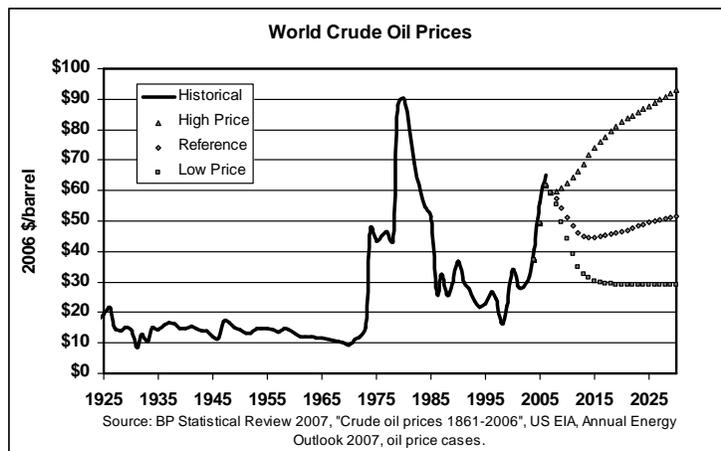


Figure 1. World Crude Oil Prices: History and Projections.

Today the future price of oil is as uncertain as it has ever been. There are five key sources of long run oil market uncertainty¹:

1. the degree to which OPEC producers will expand production,

¹ These omit the sources of shorter-run oil price uncertainty or volatility due to supply or demand shocks.

2. the extent of conventional oil resources and the rate at which they can be produced (oil peaking),
3. the ability of other sources of energy for transportation (unconventional fossil fuels, biofuels, electricity and hydrogen) to compete with petroleum fuels,
4. the extent to which nations will implement policies to increase energy efficiency in transportation and discourage increased demand through carbon taxes and carbon cap-and-trade systems, and
5. the rate of demand growth from global economic development and “motorization.”

The first source of uncertainty reflects the fact that the order of magnitude difference between short-run and long-run price elasticities of oil demand and supply gives OPEC producers a wide range of choice of production strategies. Inelastic short-run demand and non-OPEC supply allow much higher prices in the over a period of a year or two than can be sustained for a decade. Years of extremely high prices are therefore likely to be followed by years of relatively low prices. On the other hand, OPEC could strive to maintain moderately high prices within a target range and obtain similar gross revenues (Gately, 2003). As a consequence, predicting future oil prices is nearly impossible.

The second source of uncertainty is the dependence of OPEC and rest-of-world oil producers on the indefinite quantity of conventional oil resources that exists. There is very substantial uncertainty about these quantities, as reflected in the wide uncertainty band for estimates produced by the U.S. Geological Survey’s 2000 assessment (table 2): a 90% confidence interval ranges from 2 to 4 trillion barrels (Ahlbrandt et al., 2006). If the lower bound is more correct, supplies from non-OPEC countries are now beginning to peak and OPEC itself possesses limited resources. Thus, unconventional sources of liquid fuels must be developed rapidly and massively if the world’s growing demand for liquid hydrocarbon fuels is to be accommodated. If the upper bound estimate is more correct, the non-OPEC peak may not come for two decades and global conventional oil production might not peak until 2050, leaving time to develop unconventional resources and increase energy efficiency at a more moderate pace (Greene, Hopson and Li, 2005).

Table 2. USGS Estimates of World Conventional Petroleum Resources through 2025

	Oil				Natural Gas Liquids				Total Petroleum			
	95%	50%	5%	Mean	95%	50%	5%	Mean	95%	50%	5%	Mean
Undiscovered	394	683	1202	725	101	196	387	214	495	879	1589	939
Res. Growth	255	675	1094	675	26	55	84	55	281	730	1178	730
Proved Res.	884	884	884	884	75	75	75	75	959	959	959	959
Cum Prod.	710	710	710	710	7	7	7	7	717	717	717	717
TOTAL	2244	2953	3890	2994	210	334	553	351	2454	3286	4443	3345

Source: USGS, 2000, as modified to include natural gas plant liquids by Greene et al., 2003. Units: billions of barrels. Components may not add to totals due to rounding.

The AEO’s High, Reference and Low Oil price cases reflect differing judgments by oil market experts about the quantity of conventional oil that exists and the degree to which OPEC members will be willing and able to expand production. They do not, however, reflect the volatility that future oil prices will almost certainly possess.

The third and fourth sources of uncertainty reflect the potential impacts of technological change and policy on petroleum demand. Recent history suggests that these can be important. In the decade from 1976 to 1985 the world's energy markets and policymakers responded so strongly to higher oil prices and the fear of oil shortages that oil prices collapsed in 1986 (Figure 2). The future holds enormous uncertainty about how strongly the nations of the world will respond to the threat of global climate change and concerns about energy security, as well as the potential for technology to transform the energy basis for transportation.

A perspective of more than a century suggests that the technology of vehicles and fuels can produce radical changes in the transportation energy system. Since the beginning of the 19th century, the world's transportation systems have transitioned from animal power, to steam engines powered by biomass and then coal, and then to the petroleum age. Recent history, however, provides little evidence of transformational change. The U.S. transportation system is as dependent on petroleum fuels today as it was half a century ago (Figure 2). Whether the future holds yet another transition to electricity or hydrogen, or merely to conventional hydrocarbon fuels made from unconventional fossil resources remains to be seen. Given the relatively rapid progress recently achieved in battery and fuel cell technologies, and the surprising success of hybrid electric vehicles, even a model with a 25-year perspective, such as NEMS, must be capable of exploring the beginning of sweeping, technology and or policy driven transitions.

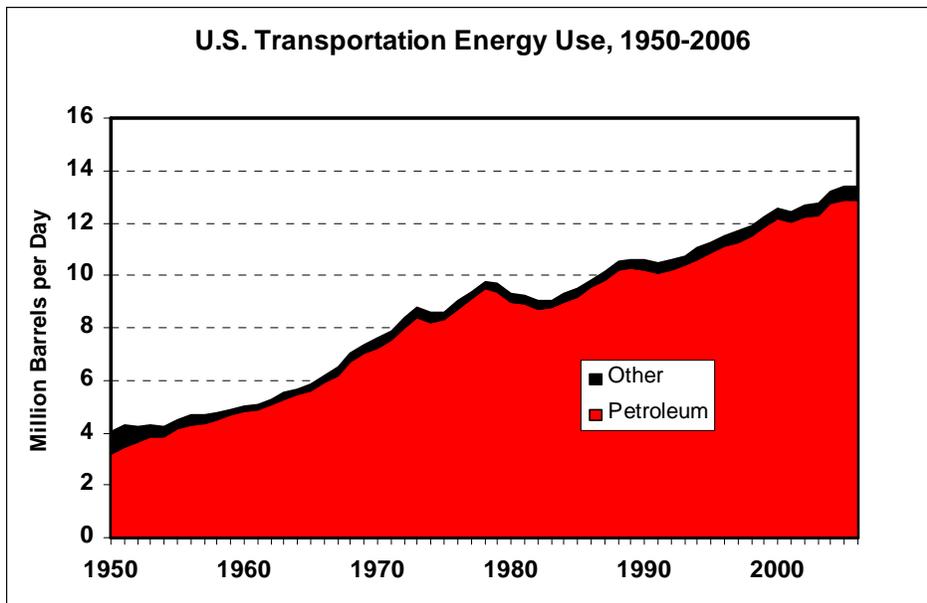


Figure 2. Transportation Energy Use by Type, 1950-2006.

Technological innovation is almost certain to have important implications for future transportation energy use through 2030. Fundamentally different technologies, such as grid-connected hybrid electric vehicles or fuel cell vehicles are not at all likely to achieve full market penetration by 2030 because of the lead time required for a new technology to penetrate new vehicle sales and then the fleet of on-road vehicles. Still, even the early stages of a fundamental transition in transportation energy use would have enormous significance. Conventional internal combustion engine technologies, as well as hybrid vehicles and biofuels, however, could have major effects by 2030. It has been estimated that technological advances could lead to an 80% improvement in conventional gasoline engine efficiency (Kasseris and Heywood, 2007) and a tripling of hybrid vehicle efficiency by 2030 (Kromer and Heywood, 2007).

The NEMS TSM does have an extensive capability to analyze exogenous technological changes in transportation energy use. Endogenous technological change is another matter. Representing the expectations of consumers and firms about technological progress is inherently difficult because predicting technological progress is a problem that modelers have yet to solve. Tools such as learning curves are calibrated retrospectively and applied to the future hypothetically. Grübler (2006) put it this way:

“The question is what instigates the technological changes that lead to energy transitions? Unfortunately, technological change is very poorly understood and even more poorly modeled. Useful generalizations can be inferred from history but prediction of technological change remains elusive.” (Grübler 2006, p. 55)

Because they are the result of political decisions, policies are also inherently uncertain, especially over a 25-year time horizon. Nonetheless, policy decisions have had a profound impact on transportation energy use and its determinants in the past. Perhaps the best example is the regulation of light-duty vehicle fuel economy. From 1978 through today, the fuel economy of new passenger cars and light trucks have closely tracked the Corporate Average Fuel Economy standards passed in 1975 (Figure 3). As a direct consequence, the average fuel economy of all light-duty vehicles in use gradually improved as vehicle stocks turned over. The standards led to a decoupling of light-duty vehicle travel and fuel use whose effects are clearly evident (Figure 4). Other policies, such as renewable fuels standards, carbon cap-and-trade policies, vehicle subsidies, low-carbon fuels standards, and research and development can have equally profound impacts.

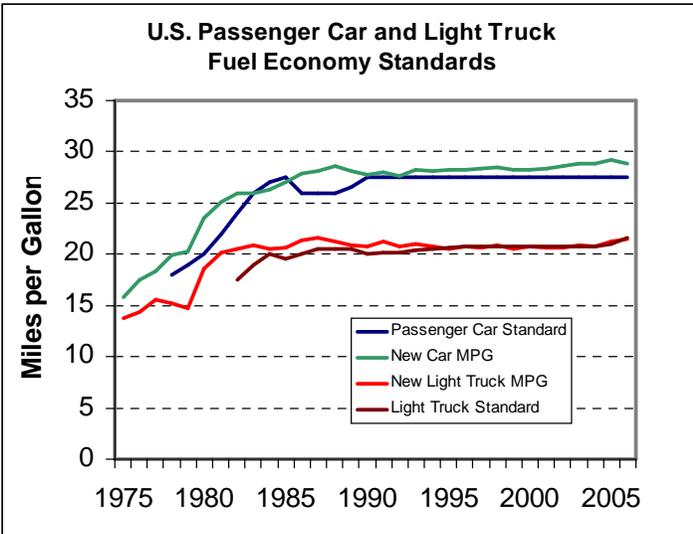


Figure 3. New Light-duty Vehicle Fuel Economy and Standards

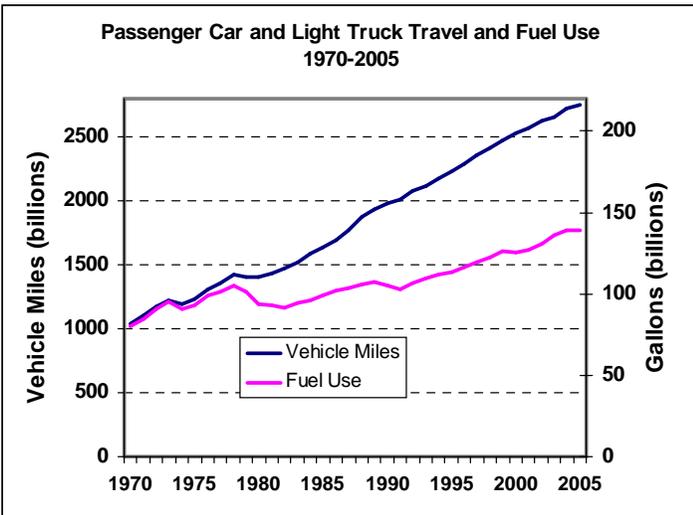


Figure 4. Decoupling of Passenger Car Travel and Fuel Use, 1970-2005

Consumers' and firms' expectations about government policies can be every bit as important as their expectations about energy prices. If biofuel producers believe that government ethanol subsidies will continue indefinitely, they will be more likely to make substantial investments in ethanol production plants. If manufacturers believe that higher mandatory fuel economy standards will be enforced, they will not only begin redesigning their product lines but may also expand their efforts in research and development.

Indeed, it appears very likely that the technology edge Japanese manufacturers currently hold in hybrid vehicle technology is due to their expectations that society would enforce increasingly stringent environmental constraints on the motor vehicle industry. However, predicting policy changes and predicting expectations about policy changes would appear to be at least as difficult as predicting technological change.

Table 3 summarizes the four sources of uncertainty and how they are represented in NEMS. In general, the predictability of these sources of uncertainty is very low, much lower than the predictability of transportation energy use itself. Furthermore, considerable methodological advances would be needed to improve predictions of these factors. In general, the NEMS model appropriately addresses these uncertainties via scenario analyses.

Table 3. Sources of Uncertainty and Their Representation in NEMS Transport Module

	Predictability	NEMS' Approach	Potential
Oil Price	Extremely low	Scenarios	Research needed
Technological Change	Extremely low	Scenarios	Doubtful
Energy Policy	Very low	Special analyses	Doubtful
Consumer Preferences	Low	History/assumptions	Research needed

III. How are transportation investment decisions made?

Transportation investments are made by consumers, governments and firms. The three groups have different objectives, use different methods for making investment decisions and dominate in different segments of the transportation sector. Investments can be broadly divided between investments in infrastructure (roads, ports, rails, and pipelines) and vehicles (cars, trucks, planes, trains and ships). Consumers dominate investments in passenger vehicles while governments make the largest share of investments in infrastructure. Firms make significant investments in both vehicles and infrastructure. Firms account for nearly all investments in pipeline infrastructure and dominate the markets for aircraft, locomotives and rail cars, as well as cargo carrying ships and trucks.

In our view, there are five key areas related to consumers' and firms' decision making that are critical for transportation energy modeling:

1. Consumers', firms' and vehicle manufacturers' decisions about new vehicle fuel economy, especially the trade-off between the increased cost of fuel economy technology and the uncertain value of future fuel savings.
2. The trade-off between vehicle energy efficiency and performance (acceleration, speed and tractive capacity).
3. Consumers' and firms' decisions in the context of major energy transitions, such as a transition from petroleum to hydrogen or electricity.
4. Decisions made chiefly by governments that affect the geography of the built environment and the transportation infrastructure in the context of which travelers and shippers make location and travel decisions.

- The certainty that consumers' preferences, the relative values they attach to attributes of vehicles and travel, will change over time. In particular, we focus on the effect of income on the value of travelers' time and the implications for the relative importance of energy costs versus time spent traveling. A similar argument can be made concerning the value density of commodities and the modal choices of shippers.

The market for fuel economy

The actual mechanisms by which consumers make vehicle purchase decisions with reference to fuel economy are relatively poorly understood. Recent research indicates that the ideal model of fully informed economically rational decision making does not correspond to the way real consumers' make decisions about fuel economy.

A U.S. Department of Energy (Opinion Research Corporation, 2004) survey asked half of the respondents what they would pay for a vehicle that saved \$400/year in fuel while the other half were asked how much they would have to save annually in fuel to justify paying an extra \$1,200 for a more fuel efficient vehicle. Payback periods can be calculated by dividing the mean (or median) willingness to pay by the \$400 in fuel savings, and dividing the mean or median expected fuel savings into the \$1,200 additional vehicle cost. The response category "None" was interpreted to mean zero. Consumers typically required payback periods between 1.5 and two years (Figure 5). However, the response category "None" includes both non-responses and consumers who would not pay anything more or would not require any fuel savings. Excluding the response category "None" results in payback periods between 1.8 and 2.6 years. These estimates are considered more correct than those that include the category "None".

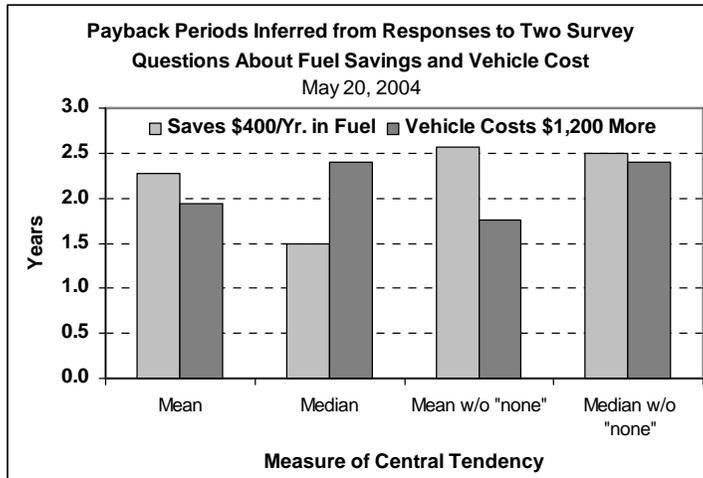


Figure 5. Inferred Payback Periods for Fuel Economy Improvement (ORC, 2004).

As a practical matter, the concept that consumers will pay for 2-4 years of fuel savings may be just a way of expressing consumers' uncertainty and loss aversion. Uncertainty about the value of future fuel savings and loss aversion can explain consumers' apparent lack of interest in fuel economy improvement. Uncertainty about the value of future fuel savings is caused by a number of factors. Despite the fact that every new vehicle carries a prominent fuel economy label, consumers do not trust the accuracy of these estimates, and for good reason. The fuel economy any individual will realize depends on traffic conditions (stop-and-go versus free-flowing) the individual's driving style (aggressive versus defensive), vehicle maintenance, climate and topography among other factors. In addition, consumers also do not know with certainty what the future price of fuel will be. They are not certain about how much driving they will do, how long their vehicle will last, and a number of other factors. Consumers are also not sure what precisely they are paying, or trading off for increased fuel economy. As a result, the net present value of an investment in fuel economy is not a single number but rather a probability distribution. Consumers, however, are known to be loss averse and will put greater weight on potential losses than gains. Uncertainty plus loss aversion appears to be a plausible alternative model of consumer decision making about fuel economy.

Using data from a recent National Academy of Sciences (NRC, 2002) study of the costs and benefits of fuel economy improvement, Greene et al. (2007) showed that uncertainty plus loss aversion could lead to a significant market failure with respect to automotive fuel economy. A passenger car fuel economy improvement from 28 to 35 miles per gallon that appeared to offer \$400 in net present value became -\$30 when uncertainty and typical consumer loss aversion were taken into account. In light of the uncertainty/loss aversion hypothesis, consumers' apparent 2-year payback requirement does not prove that consumers are not rational (in the economic sense). Instead, the uncertainty/loss aversion explanation implies that they are rational but recognize the very large uncertainties in the choice they face, and they are loss averse. If this hypothesis is valid, correctly representing consumers' uncertain expectations and loss aversion could be essential to accurately representing how real world markets function.

Evidence from an in depth survey of the car-buying histories of 57 California households indicates that, in fact, consumers do not use methods such as payback periods or present value discounting to evaluate fuel economy differences when choosing a new vehicle (Turrentine and Kurani, 2005). As a general rule, consumers in the survey did not make any kind of formal evaluation of future economic benefits. Turrentine and Kurani's findings based on a non-representative sample of California households are generally supported by the results of a 1,030 household, May 2007 national random sample survey. In that survey, 39% of respondents indicated that they did not consider fuel economy at all in their last vehicle purchase (Opinion Research, 2007). Of those who did, only 14% mentioned taking economic factors such as fuel costs or gasoline prices into consideration. Even with the much higher gasoline prices of summer 2007, the rational economic model of consumer decision making was not in evidence.

These studies demonstrate how little we know about the ways real consumers and firms actually make decisions about transportation energy related investments. At the same

time, it emphasizes the importance of a realistic representation of consumers' and firms' decision making to making predictions about market outcomes and analyzing the impacts of policies such as fuel economy standards.

For purposes of prediction, the use of short payback periods or high discount rates may accurately simulate the uncertainty/loss aversion market failure. For purposes of policy analysis, the same methodology can lead to erroneous conclusions. The fact that consumers view future fuel savings as uncertain and are loss averse does not imply that the realized fuel savings are not real or will not be fully appreciated by consumers when they are received.² The fuel savings implications of this are relatively easily handled: simply count the full lifetime discounted present value of fuel savings rather than the myopic valuation used to simulate consumer behavior. What is more difficult is to determine what effect higher levels of fuel economy would have on consumers' surplus and vehicle sales. If fuel economy standards raise MPG to levels that would be optimal considering full lifetime fuel savings but that are too high for myopic consumers, is there a loss of consumers' surplus? Will vehicle sales decline? Will manufacturers lose revenue? These are important questions for policy analysis to which we do not have firm answers at the present time.

Until recently, it was assumed that firms, in contrast to individual consumers, acted as fully informed, economically rational decision makers, basing their choices of vehicles and fuels on net present values. The Japanese government, however, directly challenged this assumption in establishing fuel economy standards for heavy trucks (Wani, 2007), in effect asserting that the fuel economy market failure might extend to firms' decisions about freight-hauling vehicles. Whether this view is correct is not known due to the lack of relevant research on the subject. In general, however, it seems likely that the larger the firm and the larger the share of energy in total costs, the more care will be taken in making decisions about energy efficiency. For example, fuel can comprise as little as 15% of the costs of airlines when oil prices are low and as much as 30% when prices are high. In either case, there is a strong economic incentive for airlines to make rational decisions about aircraft efficiency and a strong incentive for the two major world aircraft manufacturers to adopt cost-effective energy efficient technologies. The fact that air travel energy intensities have steadily declined at an average rate of over 3% per year over the past 35 years, while heavy truck and light-duty vehicle efficiencies decreased at less than 1% per year, is consistent with the hypothesis that the larger the firm and the more significant fuel costs, the greater the tendency to apply technological advances to

² This assertion that the *ex ante* valuation of fuel economy under uncertainty by a prospective car buyer may differ from the *ex post* valuation during vehicle operation would follow from a variety of behavioral models, including hyperbolic discounting. Consistent with the assertion, Toyota officials have observed that even though rated vehicle fuel economy has not generally been high on the list of factors determining consumers' new vehicle purchase choices in the past, achieved fuel economy has proven to be relevant for the subsequent level of consumer satisfaction reported by new car owners. Recognizing this and with an eye toward long-term customer satisfaction, certain manufacturers have incorporated added fuel economy technology in their vehicles, but have been understated about fuel economy in marketing, even for hybrid vehicles. Instead, they have marketed the efficiency attributes of those vehicles primarily in terms their associated environmental friendliness and technological sophistication (as well as emphasizing the usual attributes of stylishness, safety, performance and reliability).

increasing energy efficiency. Nonetheless, energy decision making by transportation firms has been too little studied to draw firm conclusions at this time.

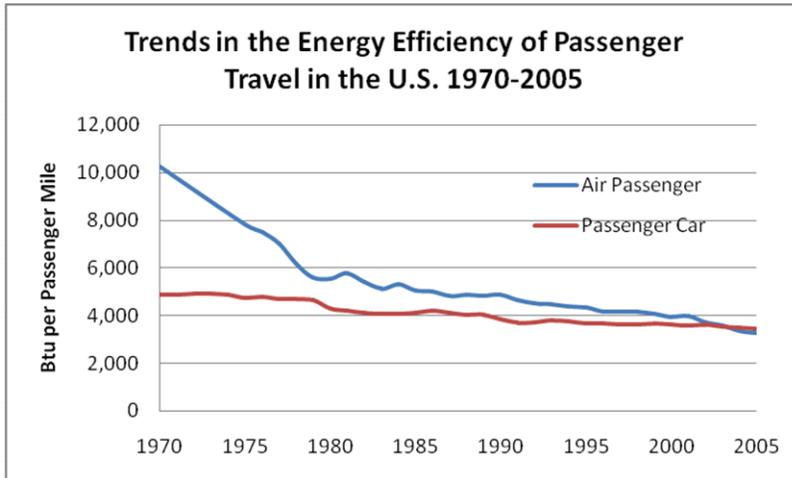


Figure 6. Energy Intensity Trends of Automobile and Air Passenger Travel, 1970-2005. Source: Davis and Diegel (2007), tables 2-13 and 2-14.

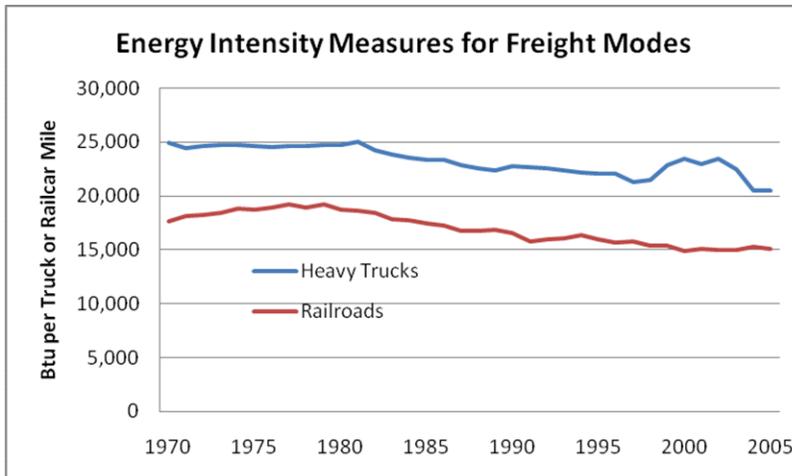


Figure 7. Energy Intensity Measures of Freight Vehicles, 1970-2005. Source: Davis and Diegel (2007) table 2-16.

Performance, weight and fuel economy

From an engineering perspective, fuel economy can be directly traded off for increased vehicle power and weight. Indeed, that is precisely what has happened in the light-duty vehicle market over the past 25 years. Technology that could have increased fuel economy has been adopted and applied to vehicles to enhance performance. Fuel

economy remained nearly constant (+2%) while vehicle horsepower increased +117% and vehicle weight increased +29%.

Econometric analyses of the trade-off between fuel economy, horsepower and weight have a reasonable chance of accurately measuring the rates at which these attributes are valued in the marketplace. Thus, calibration of the NEMS model has a good chance of accurately simulating market behavior. The chance is only good because of the strong correlation between performance and other vehicle attributes, such as price and other luxury features. For prediction, this could be a sound modeling method. For policy analysis, however, this method may be deficient. The reason is that much of the utility of power and mass may be relative rather than absolute. A consumer buying a heavier vehicle in order to gain a safety advantage in the event of a collision with another vehicle is imposing an external cost on other highway users. This implies that the market solution will be vehicles that are too heavy from the perspective of a social welfare optimum. While some of the utility of horsepower is clearly absolute, some of it is almost certainly relative. Why else would manufacturers advertise the “largest engine in its class” or “the most horsepower in its class”? Empirically estimated trade-off rates may accurately predict consumer behavior, but in light of these relative utility externalities they will also overestimate the consumer surplus losses generated by trading off weight and performance for fuel economy. This could lead to incorrect assessments of the costs and benefits of key policies such as fuel economy standards or tax incentives.

These considerations of relative utility, however, raise complex issues at the forefront of economic descriptive and welfare theory, regarding the endogeneity and interdependence of individual preferences. Work is underway on the characterization and estimation of such preferences, and effective schemes for modeling them are only in the early phases.³

Decision making in major energy transitions

Energy transitions from one major technological system and fuel to another, such as vehicle transitions from petroleum to hydrogen or electricity, by their nature involve substantial, even radical change over long time scales. As such, expectations about the prospects of these changes are critical for economic behavior in the transportation sector. The likelihood of potentially drastically different fuel or vehicle prices, the prospects for new fuel and technological choices, the expected availability of supporting (production, delivery and retailing) infrastructures, and the anticipated thrust of social priorities and policy incentives will all influence consumers' and firms' decisions in the context of major energy transitions. In cases where oil prices, markets, technologies and policies change smoothly and gradually, such as in many of the long-term energy outlooks projected with models like NEMS, the use of adaptive and other limited-foresight forms of expectations may lead to outcomes little-different from the use of perfect or long-term

³ See, e.g. Postlewaite 1998: “There has traditionally been a reluctance to include such concerns primarily because models that included them often allow such a broad range of behavior that there are few, if any, restrictions on equilibrium behavior and, hence, such models would have little or no predictive power.”

foresight. Historically-based extrapolations in these cases are likely to produce a reasonably accurate prediction of future outcomes and so limited foresight may also provide a plausible description of actual firm and consumer behavior. In contrast, in the face of sweeping transitions not only may the future be very unlike the present, but in some key periods the change may be rapid and “disruptive.”⁴ It would not be reasonable for economic agents to assume the future will necessarily be much like the present, nor would it be reasonable for modelers to assume that firms and consumers are incapable of anticipating likely changes. This is the essential challenge for modeling foresight in transition analyses: limited foresight assumes agents are consistently unable to anticipate even seemingly-obvious sea changes, and biases the analysis against change. However, since the scope and breadth of change is so great, perfect foresight by firms and consumers is also problematic. Exploring a range of approaches may best highlight the importance and implications of expectations.

Long-run expectations regarding transitions will play the greatest role for firms making large fixed investments in long-lived infrastructure, such as in pipelines and fuel production plants, or in new vehicle development, certification and production. Consumers, in turn, when considering investments in new vehicle/fuel technology are known to be attentive to expected fuel prices, anticipated vehicle performance and reliability, the likely future development of supporting refueling and vehicle maintenance infrastructure, and the projected future resale market for the vehicle. But the effective life of their vehicle investment is shorter, so they need not anticipate so far into the possible transition. As discussed at length in the above section on the market for vehicle fuel economy, evidence supports the conclusion that the applicable time horizon for actual consumer expectations is ordinarily short, compared to the functional lifetime of the vehicle. It is certainly short compared to the expected lifetime of many major infrastructural investments. Many of the factors of concern to new vehicle buyers, including expected reliability, retail fuel availability and vehicle-value in use or resale, are signaled to them by the market share for the new vehicle type. Thus consumers, when considering a new vehicle type, must effectively observe and project the future market shares, i.e. vehicle choices by many other consumers in their vicinity and in the market as a whole. This need for consumers and firms to form expectations not just about future prices, but about the future actions of other firms and consumers is a particularly prevalent challenge in transition analysis.

⁴ For a discussion of disruptive technologies, see the defining article by Bower and Christensen (1995) and the ensuing dialog. This literature emphasizes the organizational challenges posed to incumbent firms in managing disruptive change and new technologies, even when those technologies and their capabilities are largely “foreseen” by firms. The key factor identified by Bower and Christensen as leading to firm failures in this context is the tendency of established firms to follow *too* closely the requests of the majority of their current customers and the products they will *currently* accept, without being adequately attentive to the prospects for emerging markets, niche markets, and the future needs of their customers. Thus, to manage and succeed in change, Bower and Christensen call for firms to be far more foresighted and forward-looking than their customers may be. Automotive firms are considered prime examples of those facing this challenge.

Spatial structure, infrastructure and transportation choices

The demand for transportation services is strongly influenced by land development decisions and infrastructure investments. Land development decisions very likely involve principle agent market failures, with developers making decisions such as whether or not to include sidewalks or bike paths for the ultimate inhabitants of neighborhoods. Transportation decisions are also strongly influenced by infrastructure investments made by government agencies rather than private markets. A key feature of governments' transportation infrastructure decisions is the predominant provision of highways as public goods without accounting for external costs such as traffic congestion or the uncompensated portion of traffic crashes. NEMS handles these factors by holding public policies constant. However, in the future these policies could change affecting both the rates of growth of transportation demand and its modal distribution.

Income, the value of time and transportation choices

In most but not all cases, the NEMS Transportation Sector model assumes that key economic parameters, such as price elasticities, remain constant throughout the forecast period. In many cases this is a reasonable approximation. However, Small and van Dender (2007) have recently shown that one key parameter, the fuel cost per mile elasticity of vehicle travel, is strongly affected by income level. Income appears to affect travel behavior both through ability to pay and the value of time. In general, as incomes rise, the value of time increases, shifting consumer preferences to faster modes and reducing the significance of monetary costs relative to time costs in travel decisions. Similarly on the freight side, as the value of commodities increases relative to their mass (so-called dematerialization of production) shippers preferences appear to shift in favor of faster, more reliable and more flexible rather than cheaper modes. As the time frame of NEMS forecasts increases, greater attention will need to be paid to how key parameter values may change as incomes rise and production dematerializes.

“Economics is a leading example of uncertain knowledge; it is knowledge, yet it is evidently uncertain.” Hicks p. 2.

IV. Modeling Uncertainty and Expectations

Modeling expectations is a complex and evolving field. In addition to perfect foresight, various methods of representing rational expectations as a function of historical experience have been developed. Recognizing that economic agents' economic behavior may fall short of perfect rationality, various forms of limited foresight have also been developed. Initially, economists favored adaptive expectation models that could be readily calibrated to historical data. These simple approaches were eventually replaced by rational expectation methods, but there has recently been renewed interest in modeling imperfect foresight.

All of methods proposed to date pose difficulties for economic modelers. Perfect foresight and rational expectation models have the advantage of retaining many of the

economic efficiency properties of classical models of market equilibrium but are generally regarded as unrealistic. Adaptive expectation and imperfect foresight models suffer from the lack of a clear theoretical context. Their choice and calibration therefore can be ambiguous. At the same time, predicted outcomes can be quite sensitive to precisely which forms of imperfect expectations are employed and how they are calibrated.

Finally, models with imperfect foresight and imperfect expectations can lead to chaotic behavior. Whether such behavior more accurately represents reality remains an open question. Nonetheless, use of such models creates at least the potential to conclude that markets can be manipulated and outcomes controlled by exploiting the imperfections in foresight and expectations. This implies that great care should be taken to insure that the representations of imperfect expectations employed are indeed correct.

IV.2 Imperfect Expectations and Various forms of Limited Foresight

Limited foresight expectations generally assume that agents have incomplete information not just about the future, but about the structure and workings of the economy.

Adaptive expectations usually assume that forecasts of a given economic variable are formed based on past observations of that same variable alone. Forms of adaptive expectations include static, simple adaptive, extrapolative, regressive, and unrestricted distributed lag (Jacobs and Jones 1977). Let $E_t P_{t+k}$ denote the expected value at time t of a variable such as price k periods in the future, and let P_t be the actual realized value of that variable at any time t . Static, or completely myopic expectations assume that the best predictor of the future is the current value⁵: $E_t P_{t+1} = P_t$. The simple adaptive expectations model is typically a first-order partial adjustment of expectations based on the current periods error (Parkin 1988):

$$E_t P_{t+1} = E_{t-1} P_t + b (P_t - E_{t-1} P_t).$$

This common Koyck-lag form implies that expectations are a geometric weighted average of all prior observations.⁶ Higher order error learning models (e.g. Carlson and Parkin 1975) form expectations based on a weighted average of prior forecasting errors:

$$E_t P_{t+1} = E_{t-1} P_t + \sum_{\tau}^n b_{\tau} (P_{t-\tau} - E_{t-\tau-1} P_{t-\tau})$$

Ideally, adaptive expectations parameters are empirically based. For the groundbreaking work in inflation expectations, the parameters of such partial adjustment models were estimated from survey data regarding actual price expectations (Carlson and Parkin 1975). More generally, however, expectations of agents are not directly observable, and may at best be inferred from their behavior. One appealing and practical attribute of the Koyck (1954) transformation for first order adaptive expectations is its ease of empirical

⁵ A simple variant of static expectations is that the price (or other unknown variable) follows an AR(1) process: $E_t P_{t+1} = a_0 + a_1 P_t$

⁶ That is: $E_t P_{t+1} = \sum_{\tau=0}^{\infty} b(1-b)^{\tau} P_{t-\tau}$

application: parameters can be estimated solely from observed prior values of the variable, no information on prior expectations is needed.

IV.3 Perfect Foresight and Rational Expectations

Perfect foresight models which are generally deterministic (non-stochastic) allow expectations to match actual realized values: $E_t P_{t+1} = P_{t+1}$. For technical parameters such as the assumed technical efficiency of a conversion process, this assumption is not usually controversial or even noted. For future market prices, demands, and for future technological performance parameters in cases of endogenous technological learning, or in general for any endogenous outcomes of the model, the perfect foresight approach is subject to greater question. However, it is commonly applied because it is a natural outcome of the simultaneous solution of the complete dynamic planning problem.

Rational expectations, originally proposed by Muth (1960,1961), are the analog of perfect foresight in the context of explicit uncertainty. If the future value of a variable has mean \underline{P}_{t+1} and random error e_{t+1} , that is $P_{t+1} = \underline{P}_{t+1} + e_{t+1}$, an agent with rational expectations has perfect information about the mean (and distribution).

Both perfect foresight and rational expectations have the considerable advantage that they are “model-consistent,” in that agents are assumed to possess all the information contained in the model. A guiding principle is that outcomes being forecast by the agents in the model do not differ systematically from the equilibrium outcome, and firms and consumers to not make systematic errors. Alternative approaches to model-consistent expectations necessarily imply that the modeler, and thereby the planners, have information that is unavailable to or unused by consumers and producers. These foresighted methods are also advocated as being fundamentally consistent with the principal theoretical construct underlying of most of microeconomics, that agents seek to maximize value to themselves given their available information, abilities, and resources. Thus, “rational expectations is the application of the principle of rational behavior to the acquisition and processing of information and to the formation of expectations” (Maddock and Carter 1982:51).

IV.4 Historical perspective on approaches to expectations in economic analysis

The history of expectations modeling in macro economics is one of early dominance of imperfect expectations followed by its nearly complete replacement with rational expectations. Recently there is some renewed interest in modeling imperfect foresight.

Virtually all early work in macro-economics emphasized how various forms of imperfect expectations influence economic outcomes and the role of policy. Parkin’s review (1988) reports that “the adaptive expectations hypothesis became popular for and was barely challenged from the middle 1950s through the late 1960s.” It remained in extensive use into the 1970s until the rational expectations hypothesis became dominant. Jacobs and Jones (1977) noted that in early macroeconomic work often the selection among these

adaptive approaches was “somewhat ad hoc rather than based on the statistical properties of the resulting forecast.” Parkin (1988:20-21) cites three reasons for the original appeal of the adaptive expectations approach, all of which seem to be echoed by the current advocates of limited foresight in energy-economic modeling: it was intuitively appealing as descriptive of a learning process; it was empirically easy to employ (at least in the simple Koyck lag form that eliminates unobserved expectations from the regression); and it seemed to often “work” (generating reasonable parameters with a high degree of explanatory power). Also, compared to perfect foresight or rational expectation it seemed to be much more tractable analytically.

The original introduction of rational expectations was controversial, because it seemed to imply enormous information requirements and information processing capability on the part of individual economic agents. However, the support in the economics discipline for imperfect foresight, and adaptive expectations in particular, diminished as Muth (1960) and Lucas (1972) pointed out key theoretical flaws in the approach, including implications of suboptimality. While originally controversial, Romer’s text (Romer 2006:277) now notes “Today, this assumption of rational expectations seems no more peculiar than the assumption that individuals maximize utility.” To the extent that the principles of rational behavior are now being questioned, then this motivation for rational expectations may be diminished. Conlisk (1996) surveys the evidence for bounded rationality in economics, and argues that there are strong motivations for supplementing, if not replacing, the rational expectations approach. However, a theoretically coherent and empirically validated replacement is not yet readily available.

The latest research supports and develops approaches using “heterogeneous expectations,” under which rational expectations and adaptive expectations co-exist in the model for different groups of agents (e.g., Branch 2004, Brock and Hommes 1997, Carroll 2003). For example, highly-informed firms or expert individuals may be rational in expectations, and lead the opinions of adopters. However, these experimental models have a high degree of complexity and behavior that is only just being explored (e.g. Branch and McGough 2004).

“Much of the work of economists is concerned with the future, with forecasts and with planning. But forecasts are trivial and planning is useless unless they are based on fact; and the facts which are at our disposal are facts of the past.”
Hicks, p. 62

V. How are Expectations of the Future Formed?

V.1 Empirical, experimental, or theoretical support for the different approaches

Expectations formation has been studied with survey data (Lovell 1986), empirical data on economic behavior, and experimental data (e.g. Plott and Sunder 1988). The evidence is mixed. Naish (1993:3) argues that “empirical tests of the rational expectations

hypothesis have proved largely unfavorable,” citing the reviews of Lovell (1986), Frankel and Froot (1987) and Jacobs and Jones (1980). In contrast, (Sargent 2007) and others note the repeated validation of the efficient markets theory of stock prices. One implication of rational expectations is that stock prices follow a random walk. Sargent notes that literally hundreds of tests have been conducted and “the tests tend to support the theory quite strongly.”

Hey (1994) used an experimental approach to investigate whether expectations are formed rationally or adaptively, and concluded that there was evidence for a mixed approach. Chow (1989) tested whether stock price data and dividends are related to one another in a manner conforming to the present value model under rational expectations. He strongly rejected one important implication of the present value model under rational expectations but found that under adaptive expectations that model can explain the data well.

Naish’s principal claim, based on simulations, is that adaptive expectations are very close to being optimal, for a wide range of parameter values and certain model types. If losses to firms or agents with adaptive expectations are generally small, Naish argues that the substantially lower information and analytical costs of adaptive forecasting would make it a generally efficient strategy for economic agents.⁷ He specifically suggests that “in an imperfectly competitive world, where firms have different access to, and different abilities to process information, universal rational behavior would be very unlikely.” (Naish 1993:21)

V.2 Some Examples of Expectations in energy-economic modeling

The majority of large energy-economic models employ perfect foresight (complete information) approaches to solve for dynamic market outcomes. There is growing interest in limited foresight approaches, perhaps because of expanded interest in behavioral economics and known limitations of the rationality hypothesis. Some extremely large and heterogeneous models, such as NEMS, employ solution algorithms that solve the model block-by-block, and pass current and future (dynamic) information among blocks using rules that imply imperfect foresight. In general, perfect foresight in a dynamic model requires the simultaneous solution and equilibration of all components over time.⁸ When this is not computationally tractable, some form of limited information passing and foresight allows a solution, and limited foresight becomes a computational necessity. Some new models are taking hybrid approaches to limited foresight with technological learning (e.g. Hedenus et al. 2006, Kouvaritakis et al 2000).

⁷ However, Naish also cleverly notes that individual agents cannot be believed to “rationally” choose between adaptive or rational expectations-based behavior in a manner that minimizes the sum of their analytical costs and performance losses, since that choice would first involve the costly full analysis of both strategies!

⁸ Future conditions must be passed backward to the present to inform current investments, and current long-lived decisions must be reflected forward on the determination of future conditions.

Hedenus et al. (2006) describe results from a energy systems model with learning (induced technological change) and limited foresight. As they point out, limited foresight restores convexity to the optimization problem with learning-by-doing (by essentially omitting it from the planning problem of un-foresighted firms), and also yields path-dependent outcomes that can be difficult to explore in foresighted optimization models. However, the details of their limited foresight approach are relegated to an unpublished reference. There is little basis on which to evaluate their claim that, while non-optimal from a social planners perspective, the limited foresight approach has the advantage of being “better suited for simulating market behavior” (p. 42).

VI. How are expectations about the future formed in the TSM of NEMS?

In general, the Transportation Sector Module limits its formal modeling of consumer and investor expectations to the question of future fuel prices. In the Light-Duty Vehicle (LDV) module, for example, manufacturers base their decisions about adoption of fuel economy technologies partly on their expectations of future fuel prices. A type of linear extrapolation is used to calculate expected future prices. The difference between the five-year moving average of fuel prices three years ago and four years ago (non-centered) is used as a hypothetical annual price change. If the change is negative, a value of 0 is used instead. The expected price t -years ahead is t times the calculated annual price change. The LDV module also includes four adjustment factors for learning, but these appear to be exogenously specified.

The representation of alternative fuel vehicle markets in the LDV module also includes a feedback mechanism from alternative fuel market shares to fuel availability. The number of alternative fuel stations is a function of the current market share of the fuel, reflecting myopic expectations.

In the Aircraft Fleet Efficiency submodule and the Freight Truck Stock Adjustment submodule, a price threshold approach is used to represent the expectations of manufacturers of transportation equipment. Once the price of fuel exceeds an exogenously specified a threshold or trigger value, a technology that has been exogenously determined to be ready for large-scale market introduction on or before the year in question is introduced. The market penetration of that technology then follows a logistic market penetration function that is a function of time but also dependent on the price of fuel relative to the threshold price. In the aircraft and truck freight modules, the current price of fuel is used, implying static expectations.

“The more characteristic economic problems are problems of change, of growth and retrogression, and of fluctuation. The extent to which these can be reduced into scientific terms is rather limited; for at every stage in an economic process new things are happening, things which have not happened before – at the most

they are rather like what has happened before.” Sir John Hicks, *Causality in Economics*, p. xi.

VII. Observations on Modeling Foresight in Transportation Investments

VII.1 Key Uncertainties for Which Expectations Are Important

There is no doubt that key factors that will determine future transportation energy use are highly uncertain: the price of petroleum, the rate and direction of technological change, government policies with respect to climate change and oil dependence, and consumers' preferences and firm behavior. The answers to questions such as the following will undoubtedly have a profound impact on the quantities and types of energy used by the world's transport systems and on the prices paid for energy, as well.

- Oil prices:
 - How much conventional oil is there and at what rate can it be produced?
 - Can and will OPEC expand its production to meet growing transport demand at moderate prices?
- Technology:
 - Can fuel cell vehicles be competitive with hybrids and advanced ICEs?
 - Can batteries be improved to compete, making grid electricity a source of energy for transportation?
 - Can carbon sequestration be practical, making fossil energy compatible with mitigating climate change?
 - How much can biofuel production for transportation be increased?
- Government Policy:
 - Will the world adopt and enforce strong GHG policies?
 - Will countries like the U.S. and China adopt policies that achieve oil independence?
- Consumer and firm behavior:
 - Will consumers accept or prefer vehicles that can take energy from the grid, or are in other ways different?
 - Will firms invest in new technology development and production facilities?

The remainder of this section reviews the major considerations in choosing among approaches to expectations.

VII.2 Challenges and Merits of Using Each Expectations Approach

Perfect Foresight/Rational Expectations

A merit of the perfect foresight or rational expectations approach (given embedded uncertainty) is that the results report self-consistent and economically efficient behavior. For policy and planning purposes, the results may be interpreted as a least cost outcome. Usually perfect information approaches pose greater computational challenges, since they

require the simultaneous solution of all time periods and markets. Rational expectations models require modern solution methods for stochastic optimization. It must be acknowledged that a number of large models using limited foresight do so because of the reduced computational burden and (often) eased convergence, not because they are employing a necessarily more sound theoretical or empirical foundation. Neither perfect foresight nor rational expectations approaches avoid the potential problems of multiple equilibria (e.g. Deissenberg 2003, Obstfeld 1984), which occur particularly in cases of self-reinforcing energy-economic systems.

Adaptive expectations and Imperfect Foresight: Benchmarking Expectations

A large challenge posed by the imperfect foresight approach is grounding the model's representation of expectations formation in our best understanding of how economic agents actually perceive and anticipate the future. There are a multiplicity of approaches to expectations formation, and modeling experience and economic theory indicate that the choice among them can strongly influence modeled outcomes. Naish (1993:3) reminds us that "as noted by Simon (1984), a primary reason the idea of rational expectations became so popular was precisely because it removed the need to conduct any empirical inquiry into how economic agents form their expectations." Arguably, introducing complex and imperfect expectations into a model should be preceded by the careful empirical analysis of the nature of those expectations. To date virtually all research on this topic has been in the area of macroeconomics, largely focusing on inflation expectations.

Macroeconomic modeling continues to pay the greatest attention to expectations, and to the implications of various specifications of expectations formations. In some cases, substantial ancillary effort is expended to specify an empirically grounded equation for expectations. For example, FRB/Global, a major global macro-economic model developed by the Federal Reserve Bank, was recently extended to allow two treatments of expectations formation: limited-information adaptive and rational. (Levin Rogers and Tryon 1997:1) "To represent limited-information expectations, FRB/US uses a core vector autoregression with auxiliary equations (cf. Brayton and Tinsley 1996; Brayton et al. 1997)" (Levin, Rogers and Tryon 1997:1) They find the method of expectations formation can have important implications for the simulation results. Other modern models which introduce limited information use the Kalman filter to make forecasts (e.g. Erceg, Guerrieri and Gust 2003)

Importance of choice of Expectations approach for modeling outcome

It is generally acknowledged that the specification of adaptive expectations can strongly influence the modeled outcome. For example, when most firms have complete information and even only some firms have adaptive expectations, a wide variety of outcomes is possible (Naish 1993:5). From this one might conclude that rational expectations is not a robust hypothesis, and that adaptive expectations are a useful explanation for business cycles and other oscillatory behavior. Alternatively, one can

view the ability of imperfect expectations to generate a wide range of outcomes as a two-edged sword.

Depending on the specification, imperfect and adaptive expectations approaches can induce a wide range of cyclical or even chaotic market outcomes over time. For example, with the simple cobweb model of market supply-demand equilibration over time, Hommes (1994) found that adaptive expectations can diminish the price fluctuations compared to what would be observed with the usual “naïve” (myopic) price expectations. However, he also found that chaotic price-quantity behavior can occur for a large class of nonlinear, monotonic supply and demand curves. In general, the careful choice of foresight specification can minimize some of this adverse behavior, by choice of lags and adjustment rate, but care is needed.

Consistent modeling and Policy Analysis Under Limited Foresight

A second important caveat for limited foresight methods is the need to avoid modeling experiments which imply that substantial gains are possible from policies which exploit the assumed systematic forecasting errors of the modeled agent. The risk here is falling afoul of the “Lucas Critique:” it is erroneous to assume that exogenous expectational or behavioral rules are invariant to policy. Furthermore, it also can be a mistake to assume markets can be manipulated by exploiting erroneous or biased expectations. Sargent (2007) points out:

“Rational expectations undermines the idea that policymakers can manipulate the economy by systematically making the public have false expectations. Robert Lucas showed that if expectations are rational, it simply is not possible for the government to manipulate those forecast errors in a predictable and reliable way for the very reason that the errors made by a rational forecaster are inherently unpredictable.”

However, under imperfect expectations, these type of direct or indirect influences on market outcomes through altering imperfect expectations might easily occur in the model. It is not clear that such impacts are actually possible to achieve. Regardless of the degree of rationality assumed for firms, consumers and their expectations, there are strong philosophical arguments for avoiding any policy analysis which assumes private agents adopt systematically non-optimal strategies with respect to the government’s policy plans and decision rules. Under this principle, even adaptive private agents should be made aware of future policies (e.g. taxes and regulations) being evaluated in the model.

VII.3. Need for a Case-dependent, Careful Exploratory Approach to Expectations

Clearly the unquestioning and universal application of any form of expectations is not fully satisfactory. Limited foresight methods continue to have intuitive appeal, and offer tantalizing promise of greater realism. But Naish’s (1993:21) final conclusion in support

of adaptive expectations actually highlights a challenge to analysts who would use that approach for important policy studies:

“Also, adaptive expectations result in a much richer model. ...with adaptive expectations there is a vast array of possible outcomes depending on many different parameters.”

Which outcome is to be trusted? It seems we must be cautious, pending further careful study of the actual formation of expectations in energy markets.

At the same time, there is growing awareness of the need to recognize some limits to rationality in economic behavior. Conlisk's (1996:692) survey summarizes four reasons why some degree of limited rationality should be represented: (1) “wide-ranging evidence that bounded rationality is important”; (2) models with bounds on rationality “have excellent success in describing economic behavior”; (3) “the conditions of a particular context may favor either bounded or unbounded rationality”; and (4) models with bounded rationality “adhere to a fundamental tenet of economics” by respecting that human cognition is a scarce resource.

Conlisk concludes with a wise call for a careful, case-dependent approach to expectations:

“The survey stresses throughout that an appropriate rationality assumption is not something to decide once for all contexts. ... As with other model ingredients, however, we in practice want to work directly with the most convenient special case which does justice to the context. The evidence and models surveyed suggest that a sensible rationality assumption will vary by context, depending on such conditions as deliberation cost, complexity, incentives, experience, and market discipline.”

There is little doubt that the expectations of consumers and firms can have important impacts on the rate and extent of changes in transportation energy use. But the question is whether incorporating more realistic representations of consumers' and producers' expectations will improve the NEMS' model's ability to accomplish its purposes of developing useful projections of future energy use and evaluating the impacts and effectiveness of energy policies. On the one hand, it seems clear that more realistic representation of decision making in energy markets would be of great value, especially for policy analyses. On the other, it seems clear that substantial additional research is needed to develop a more complete and accurate understanding of how these markets function in the real world.

References

1. Ahlbrandt, T.S., R.R. Charpentier, T.R. Kleit, J.W. Schmoker, C.J. Schenk and G.F. Ulmishek, 2005. *Global Resource Estimates from Total Petroleum Systems*, AAPG Memoir 86, American Association of Petroleum Geologists, Tulsa, Oklahoma.
2. Bower, Joseph L.; Christensen, Clayton M.. 1995. "Disruptive Technologies: Catching the Wave," *Harvard Business Review*, Jan/Feb95, 73(1):43-53.
3. Branch, William A., 2004, "The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations," *Economic Journal*, 114:592-621 (July).
4. Branch, William and McGough, Bruce (2004) "Multiple Equilibria in Heterogeneous Expectations Models," *Contributions to Macroeconomics*: Vol. 4 : Iss. 1, Article 12.
5. Brock, William A., and Cars H. Hommes, 1997, "A Rational Route to Randomness," *Econometrica*, 65(5), 1059-1095 (Sep.).
6. Carlson, John A and Parkin, J Michael, 1975. "Inflation Expectations," *Economica*, London School of Economics and Political Science, 42(166):123-38, May.
7. Carroll, Christopher D., 2003, "Macroeconomic Expectations of Households and Professional Forecasters," *Quarterly Journal of Economics*, 118(1):269-298.
8. Chow, Gregory C. 1989. "Rational Versus Adaptive Expectations in Present Value Models," *The Review of Economics and Statistics*, 71(3): 376-384 (Aug).
9. Conlisk, J., (1996), "Why Bounded Rationality?" *Journal of Economic Literature*, 34(2):669-700.
10. Davis, S.C. and S.W. Diegel, 2007. *Transportation Energy Data Book Edition 26*, ORNL-6978, Oak Ridge National Laboratory, Oak Ridge, Tennessee.
11. Energy Information Administration (EIA), 2007a. "The National Energy Modeling System: An Overview 2003", available on the internet at www.eia.doe.gov/oiaf/aeo/overview/introduction.html .
12. Energy Information Administration (EIA), 2007b. "Transportation Sector Module of the National Energy Modeling System: Model Documentation 2007", DOE/EIA-M070(2007), Office of Integrated Analysis and Forecasting, Washington, D.C., May.
13. Energy Information Administration (EIA), 2007c. *Annual Energy Review 2007*, DOE/EIA-0384(2007), U.S. Department of Energy, Washington, D.C.
14. Energy Information Administration, 2007d. *Annual Energy Outlook 2007*, DOE/EIA-0383(2007), U.S. Department of Energy, Washington, D.C.
15. Deissenberg, Christophe, Gustav Feichtinger, Willi Semmler and Franz Wirl, 2003. "Multiple Equilibria, History Dependence, and Global Dynamics in Intertemporal Optimization Models," Forthcoming in Barnett, W., C., Deissenberg, and G. Feichtinger (Eds), *Economic Complexity: Non-Linear Dynamics, Multi-agent Economies, and Learning*, ISETE Vol. 14, Elsevier, Amsterdam. August.

16. Frankel, J.A. and K.A. Froot, 1987. "Using survey data to test standard propositions regarding exchange rate expectations," *American Economic Review* 77:133-153.
17. Gately, D., 2006. "What oil export levels should we expect from OPEC?", Department of Economics, New York University, June.
18. Gordon, R.L., 1999. *Law and Macroeconomics*,
19. Greene, D.L., J. German and M.A. Delucchi, 2007. "Fuel Economy: the Case for Market Failure", manuscript, Oak Ridge National Laboratory, Oak Ridge, Tennessee, October.
20. Greene, D.L., J.L. Hopson and J. Li, 2003. "Running out of and into oil: analyzing global oil depletion and transition through 2050", ORNL/TM-2003/259, Oak Ridge National Laboratory, Oak Ridge, Tennessee.
21. Greene, D.L., J.L. Hopson and J. Li, 2006. "Have we run out of oil yet? Oil peaking analysis from an optimist's perspective", *Energy Policy*, v. 34, pp. 515-531.
22. Grübler, A., 2006. "An Historical Perspective on Global Energy Transitions", pp. 53-60 in D.L. Greene, ed., *Modeling the Oil Transition: A Summary of the Proceedings of the DOE/EPA Workshop on the Economic and Environmental Implications of Global Energy Transitions*, ORNL/TM-2007-014.
23. Hedenus, Fredrik; Azar, Christian; Lindgren, Kristian 2006. "Induced Technological Change in a Limited Foresight Optimization Model," *Energy Journal*, (Special Issue: Endogenous Technological Change), pp. 41-54.
24. Hey, John D. 1994. "Expectations formation: Rational or adaptive or . . . ?", *Journal of Economic Behavior and Organization*, 25:329-349
25. Hommes, Cars H. 1994. "Dynamics of the cobweb model with adaptive expectations and nonlinear supply and demand," *Journal of Economic Behavior and Organization* 24:315-335.
26. Hicks, J. 1979. *Causality in Economics*, Basic Books, Inc., New York.
27. International Energy Agency (IEA), 2006. *Energy Technology Perspectives 2006*, OECD, Paris.
28. Jacobs, Rodney L. and Robert A. Jones 1977. "A Bayesian Approach to Adaptive Expectations," Discussion Paper #93, University of California, Los Angeles, June.
29. Jacobs, Rodney L. and Robert A. Jones, 1980. "Price expectations in the United States: 1947-75," *American Economic Review*, 70:269-277.
30. Kasseris, E. and J.B. Heywood, 2007. "Comparative Analysis of Automotive Powertrain Choices for the Next 25 Years", SAE Technical Paper Series, no. 2007-01-1605, Society of Automotive Engineers, Warrendale, PA.
31. Kouvaritakis, N; Soria, A; Isoard, S 2000. Modelling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching," *International Journal of Global Energy Issues*. Vol. 14, no. 1/2/3/4.
32. Koyck, L.M. 1954. *Distributed Lags and Investment Analysis*, (Amsterdam: North Holland).
33. Kromer, M.A. and J.B. Heywood, 2007. "Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet", LFEE 2007-02 RP, Sloan

Formatted: Danish

Automotive Laboratory, Massachusetts Institute of Technology, Cambridge, Massachusetts, May.

34. Levin, Andrew T., John H. Rogers, and Ralph W. Tryon 1997. "A Guide to FRB/Global," International Finance Discussion papers, Number 588, Board of Governors of the Federal Reserve System, August 1997.
35. Lovell, Michael C. 1986. "Tests of the Rational Expectations Hypothesis," *American Economic Review*, 1986, 76(1):110-24. Mar.
36. Lucas, Robert (1976). "Econometric Policy Evaluation: A Critique." *Carnegie-Rochester Conference Series on Public Policy* 1: 19–46.
37. Maddock, Rodney and Michael Carter 1982. "A Child's Guide to Rational Expectations," *Journal of Economic Literature*, 20(1):39-51 (Mar., 1982).
38. Muth, J.F. 1960. "Optimal properties of exponentially weighted forecasts," *Journal of the American Statistical Association*, 5(290):299-306.
39. Muth, J.F. 1961. "Rational expectations and the theory of the price movements," *Econometrica*, 29, 315–35.
40. Naish, Howard F. 1993. "The near optimality of adaptive expectations," *Journal of Economic Behavior and Organization* 20:3-22.
41. (NRC) National Research Council. (2002). *Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards*, National Academies Press, Washington, D.C.
42. Obstfeld, Maurice 1984. "Multiple Stable Equilibria in an Optimizing Perfect-Foresight Model," *Econometrica*, Vol. 52, No. 1. (Jan., 1984), pp. 223-228.
43. Parkin, Michael 1988. "Adaptive Expectations", *The New Palgrave: a Dictionary of Economics*, John Eatwell, Murray Milgate and Peter Newman (eds.), February, 1988, pp. 20-21.
44. Postlewaite, Andrew 1998. "The social basis of interdependent preferences," *European Economic Review* 42, 779-800
45. Sargent, Thomas J., "Rational Expectations", [The Concise Encyclopedia of Economics](#), Liberty Fund, Inc. Ed. David R. Henderson. Library of Economics and Liberty. 18 November 2007.
<<http://www.econlib.org/library/Enc/RationalExpectations.html>>.
46. Small, K.A. and K. Van Dender, 2007. "Fuel efficiency and motor vehicle travel: the declining rebound effect", *The Energy Journal*, vol. 28, no. 1, pp. 25-51.
47. Romer, David 2006. *Advanced Macroeconomics*, 3rd Edition, (Boston: McGraw-Hill Irwin).
48. Wani, K., 2007. "Fuel Efficiency Standard for Heavy-Duty Vehicles in Japan", presented at the International Workshop on Fuel Efficiency Policies for Heavy-Duty Vehicles, IEA/International Transport Forum, Paris, June 21-22, Paris.